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The percentage indicates the combined amount of likely AI-generated text as well as likely AI-generated text that was also likely AI-paraphrased.

Caution: Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Detection Groups

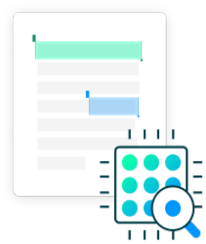
0 AI-generated only 0%
Likely AI-generated text from a large-language model.

0 AI-generated text that was AI-paraphrased 0%
Likely AI-generated text that was likely revised using an AI-paraphrase tool or word spinner.

Disclaimer
Our AI writing assessment is designed to help educators identify text that might be prepared by a generative AI tool. Our AI writing assessment may not always be accurate (i.e., our AI models may produce either false positive results or false negative results), so it should not be used as the sole basis for adverse actions against a student. It takes further scrutiny and human judgment in conjunction with an organization's application of its specific academic policies to determine whether any academic misconduct has occurred.

Frequently Asked Questions

How should I interpret Turnitin's AI writing percentage and false positives?
The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI paraphrase tool or word spinner.



False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?
Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.

SMART COMPETENCY DIAGNOSTIC AND CANDIDATE PROFILE SCORE CALCULATOR

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Abstract

This study proposes a smart and data-driven ATS-friendly.

Candidate Profile Generator and Resume Scorer to be enhanced. **R**ecruitment fairness and efficiency. Unlike traditional **.**The system, which is usually biased and time-consuming, is involved in the hiring **,**uses machine learning, NLP and text mining to **analyse** . resumes, scoring on compliance on ATS, keyword contextual experience, relevance, and experience. It also integrates **,**psychometric tests to evaluate the soft skills, behavioral characteristics, and intellectual capabilities, and an integrated candidate. profile not only on technical qualification.

The profile formed is compared to the job descriptions to.

make individual suggestions, and besides that, offer personalized. criminals build positive feedback to improve employment. Through standardized assessments in order to eliminate bias and guarantee, transparency, the system facilitates hiring in the enterprise, and campus .Placements and talent development. Its scalable design allows connecting to HR ecosystems, the future scope of which will cover on-the-fly labor market intelligence, discrimination, and more inclusive to inclusive and data-driven **multilingual assessments, recruitment.**

INTRODUCTION

The recruitment and talent evaluation is the process.
growingly becoming data intensive,
requiring tools that are good, objective and smart.
Hiring methods that are more traditional and based on the resumes and subjective judgments, tend to be biased, inefficient and ineffective.
candidate competency and job mismatches.
requirements. In an effort to conquer these issues, this study.
suggests Intelligent Competency Diagnostic and Profile Score.
Calculator incorporating resume data, ATS score and psychometric information to offer a holistic analysis of.
candidates.
The system is not just a resume parsing system.
and keyword matching with using advanced analytics, machine learning models, psychometric evaluation.
They gather the candidate information in the form of resumes, online tests, etc.
and the psychometric tests, and then input to a single.
competency profile. This is a competency profile that produces a. measurable mark, which reflects the aptness of the candidate.
to fill a particular position with both hard and soft skills.
In contrast to the traditional applicant tracking systems (ATS), which
The proposed tool will mainly concentrate on keyword matches.
framework evaluates candidates in different aspects,
and in this list is the cognitive ability, communication, problem solving capacity and domain-based expertise.

The system uses machine learning to make predictive insights, and makes certain, more precise role correlation, and decreasing human bias in the recruitment process.

RELATED WORKS

Resume / Information Extraction from Resumes
A complete architecture of information extraction of Italian. resumes (Expert Systems with Applications, 2022) ScienceDirect[1]

- This paper explains a system which divides resumes into segments. significant contents with language patterns and keywords, then implements NER (named entity recognition) to draw out competent information such as skills, education, experience of work.
- Relevance: Assistance with designing the "feature extraction" phase of your diagnosis picture; the understanding of how to dependably ,it is important to format resume.

Resume Matching / Recommendation System
Machine Learning system to automate Resume. Recommendation system (Procedia Computer Science, 2020) ScienceDirect[2]

- Owen proposes classification (resume categorization) and content, cosine similarity based recommendation and k-NN.
  etc. to shortlist according to a job description.
- Relevance: Like in your score calculator conception; you could use ranking and matching algorithms.

Classification of Resumes using Large-scale Datasets *Large Language Models and Datasets Databases (Procedia Computer Science,* 2024) ScienceDirect[3]

- Classifies resumes into with LLMs (such as BERT etc.) selections; uses a sample of resumes of about 13389. Achieved high accuracy.
- Relevance If your scoring has to do with categorization or it can be identified that there are competencies or profession types, techniques here help.

- **Psychometric / Personality / Competency Over Time**
  *Personality predictive validity of personality in a temporal manner with regard to job. voluntary turnover, high stakes and performance and career success. contexts- A longitudinal study (Personality and individual). Differences, 2023)*ScienceDirect[4]

- Personality (e.g. Big-Five traits), cognitive Measures. predicting job performance using ability, as well as using structured interviews, and life long professional success. Finds that traits like factors that are strong predictors of conscientiousness are not limited to. cognitive ability.

Relevance: In respect to your project you could take into consideration ,including measures of personality or trait in your diagnostic score; this is an indication of what is important.

- **Psychometric Needs & Behavior in Work Context** *Self-assessment of requirements and work behavior pattern:*
- *Psychometric of the Personality and Preference.*
- *Personality and Individual- Inventory-Normative (PAPI-N Differences, 2006)* ScienceDirect[5]

- speaks about PAPI-N questionnaire, which measures. psychological needs and behavior patterns at work. Job, reliability and validity test.
- Relevance: Helps know how relevant at work. You can use personality / preference tests which are designed. similar with addition of psychometric questions. in your profile.

Loddo et al. (2022), "An end-to-end framework for information extraction from Italian resumes" (*Expert Systems with Applications*).[6]

- This paper will suggest an NLP based framework that pulls out defined information automatically such as individual information, talents, and experiences in resumes.
- It underlines the issue of different formats in. Artificial intelligence is part of the solution to better resume and illustrates the benefit of machine learning. achieve robust extraction.
- Relevance: Parsing of resume is based on this. stage your competency diagnostic calculator.

Varshney et al. (2020), "A Machine Learning approach for automation of Resume Recommendation system" (*Procedia Computer Science*).[7]

- The authors create a system of resume recommendations. with the help of classification algorithms and the similarity measures. to align the resumes to job requirements.
- It focuses on efficiency as it automates the recruiting process. Resume shortlisting.

Scholz et al. (2021), "The validity and reliability of clinical judgement and decision-making skills assessment in nursing: A systematic literature review" (*Nurse Education Today*).[8]

- Inspections competency evaluation assessment tools. Concentrated on validity of various kinds as well as reliability. approaches. talks about the best practices of competency designing. assessment frameworks.
- Relevance: Provides information on how to make sure that your competency diagnostic scores are reliable, valid ,not only technically produced.

Comparative Table

Author / Year	Title (Venue)	Method / Approach	Strengths	Limitations
Zhao et al., 2021 (IRS 2021)	Embedding-based recommender for job→candidate	Fused embeddings (text + metadata) for jobs & resumes; large-scale production	Scales to production; fuses multiple features; real-world lessons	Proprietary dataset; limited reproducibility
Rosenberger, 2025 (Expert Systems Appl.)	CareerBERT: shared resume–job embeddings	BERT-based shared embedding space for resumes + ESCO taxonomy	Strong semantic alignment; standardized taxonomy	High compute cost; depends on ESCO quality
Thesai.org, 2024 (Science & Info Org.)	Enhanced Resume Screening (S-BERT + cosine)	Sentence-BERT embeddings + cosine similarity; rule-based NER	Simple, effective semantic matching; easy to implement	May miss fine-grained fields without tuning
DEEPRESUME, 2024 (RJPN Research Journal)	Deep learning-based resume parsing	End-to-end deep models (text-block classification + NER)	Handles varied layouts; reduces manual rules	Needs labeled data; domain adaptation required
Muddangala, 2024 (SSRN)	Privacy-preserving, explainable job recommender	BERT embeddings + privacy methods + explainability layer	Tackles privacy & explainability; improves trust	Working paper; may lack peer review; complex implementation

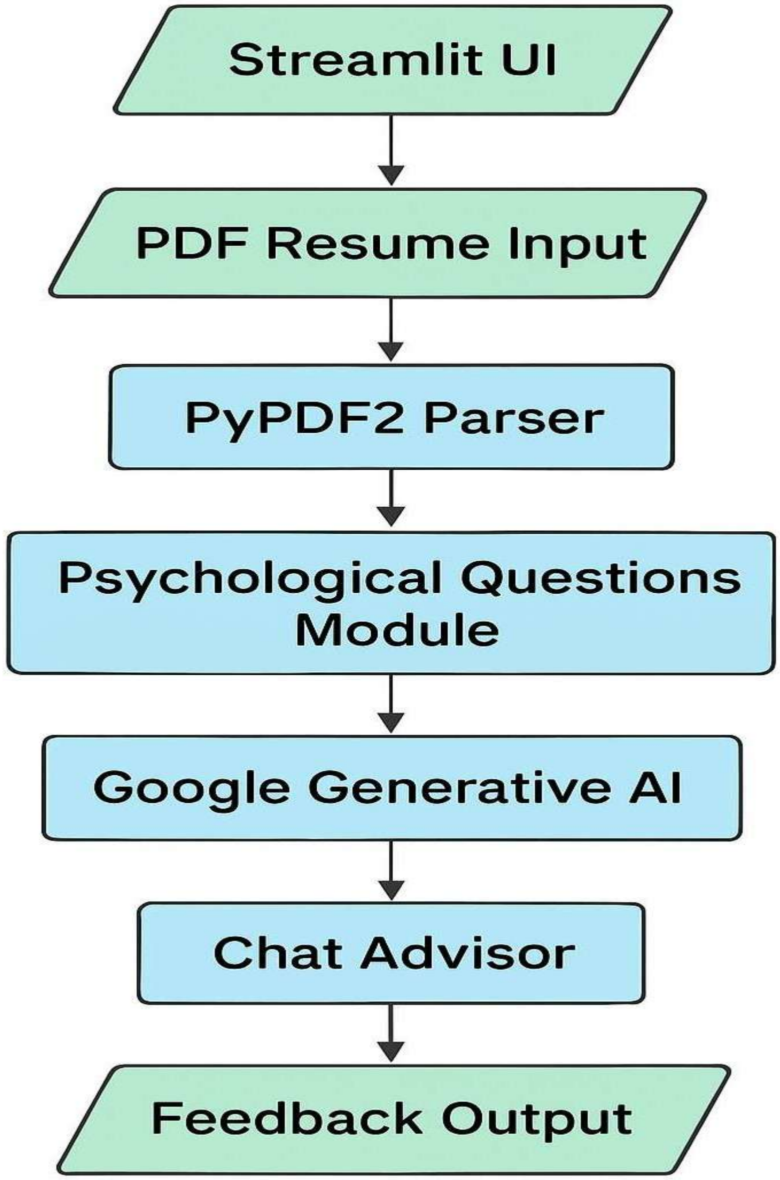
Model Architecture

The following are the highlights of the revised Advanced-ATS-Resume-Checker diagram including the psychological questions module:

- Streamlit UI: UI to provide resume, answer psychological questions, get feedback and chat with,the AI advisor.
- volt 8 PDF Resume Input: PDF resume can be uploaded by the UI.
- Py PDF 2 Parser: Parsing of text in the PDF resumes uploaded to be analyzed.
- Owen, 2012: Displays psychological questions to customers and gathers feedback about candidate further analysis. insights. Obviously, Diflearn has a prominent role in the trick's history, while Google Generative AI is grounded on the core AI engine which analyzes resume text and psychological responses, and offers ATS-like scoring,feedback, and individual support via chat.
- Chat Advisor: AI-assisted interactive conversation application on the base of Google Generative AI to create a personalized resume in real-time,psychological insights.
-
- Feedback Output: Visually presents comments that can be acted on to optimize the resume and psychological insights to the user.

This architecture will reduce the flaws of the resume analysis by incorporating the psychological responses to questions to be able to acquire more comprehensive information about the candidates.

Fig:



Architecture

The new layout of the Advanced-ATS-Resume-Checker will combine resume-checking and psychological testings so as to offer, an all-inclusive assessment of job seekers. The user will serve off an interface built with Streamlit in which user must upload their PDF resume and .respond to psychological questions that are set to provide more insight into the candidates. The extracting and preprocessing of resume is done by Py PDF2.

The content module, and user responses are collected and processed in a special psychological questions module. Both the resume information and the psychological.

Google feeds its Generative AI with inputs and provides ATS-style resume scoring, generates actionable estimated feedback and offers.

individual guidance through a chat program. This is a combined strategy, which contains the benefit that it optimizes resumes to

get through ATS and also does much more, enhances the profiles with psychological insights that enable users to enhance their professional presentation as well as personal fit to a job.

job opportunities. The system is user-friendly with the flexibility and strong AI-based analysis technique to enhance the likelihood of an interview, and concur with intelligent self-evaluation.

APIs Used and Integration

1. Overview of APIs Used

Explain the need of each API involved into the system, including resume parsing and AI analysis, and many more.

2. Resume Parsing API

Describe the API which extracts and preprocesses.

resume information (e.g. Python PDF 2 parser or any third-party resume parsing are supported).

service). Foundation Supported formats, extracted key data fields.

Therefore, (contact info, education, skills, experience), and any language or layout handling features.

3. Psychological Questions Module API

Psychological API recruiting questions module.

Reports whether another API or service is being utilized to present and collect, and examine psychological questions and answers. Include information about type of questions and processing of responses.

4.Generative AI API

Describe how Google Generative AI API was used to score resumes, creating feedback, customized chat advice, psychological. data integration. Mention methods of authentication .Form of endpoints, and artificial intelligence capabilities used.

5.API Interaction Flow

Description The flow of data between frontend and resume parser Outline the flow of data,AI API, psychological questions module. Highlight synchronous and asynchronous call, data format (JSON) and error handling.

6.Security and Authentication

Use of note authentication such as API key or OAuth token.

to secure API calls. Talk of environment variable management. for keys (e.g., in .env files).

7.API Rate Limits and Performance

Talk about anything rate limiting, latency issues and performance, integrations on the built in APIs so that it will run smoothly on the user experience..

8.Future API Integration Possibilities

Poorly obligatory section with respect to third-party API enhancements or even more AI models will be continued in the future capability.

Future Research Directions

- **Psychological Questions Integration:**

  At this moment, psychological questions are formulated, though not ,completely a part of the AI analysis workflow. Future work will address the direction towards smooth integration of psychological, resume data to create more richer holistic data, candidate evaluations.

- **Enhanced Psychological Assessment:**

  Test and experiment with psychometric tests that are proven. techniques of psychological profiling in order to make them better. quality and topicality of candidate insight out of basic question responses.

- **AI Model Training for Psychology:**

  The model can be trained using the gathered data of the patients in accordance with their age, diagnoses, and medication taken, etc., rather than relying on subjective judgments to assess the condition of a patient or the success of a treatment method used.

- **Real-Time Adaptive Questioning:**

  Create active, interactive questionnaires, which run on.

  AI to customize in greater response to applicants,and more specific psychological testing. Athenians think that morality and privacy are crucial in determining what individuals can or are not permitted to do.

- **Ethical and Privacy Considerations:**

  Privacy of research data, consent tools and ethical.

  Lines of treatment of psychological information to guarantee adherence and develop trust in users.

- **Broader Behavioral Analytics:**

  This is an extension of the earlier behavioral analytics with the primary difference of utilizing additional analysts, some of whom are business analysts, to examine the situation and consequently, develop the corrective actions.

CONCLUSION

It is important to have a close to your project summarizing what it was all about, purpose, approach and benefits, and also bringing out its, new dimensions and prospective. Here is a more elaborate and promiscuous example you may gratify: The Advanced-ATS-Resume-Checker is a project that deals with an essential, problem encountered by all applicants nowadays: can resumes be made to pass?
with the help of more and more complicated Applicant Tracking Systems (ATS) that shift a great percentage of candidates prior to human, review. PDF resume parsing is combined with the powerful. Google Generative AI The system offers a solution to intelligence of the prototype. comprehensive analysis which is a simulation of ATS, provides, active feedback and informs users on how to make their resume be best. content effectively.
The tool also provides personalisation other than mere matching of keywords, guidance through a chat system, and it assists the users know not only what needs improving, but why. This provokes a more educated and cyclical resume improvement process. The planned integration of psychological question testing tries to enlarge this overall. method by comparing qualities of the candidates and professional, qualifications, adding more value of matching the system. applicants to the suitable positions. This project is made of blocks and is scaled and could be used as a stepping block. stone to smarter, AI-based recruitment in by greater means it is able to develop together with demands of job markets and staffing, practices. Finally, it gives the job seekers extra power, technology, thus they have the potential to rise out of a competitive, environment and enlarge their chances to attain. interviews and develop their career.

REFERENCES

[1] T. Mikolov, K. Chen, G. Corrado, and J. Dean, “Efficient estimation of word representations in vector space,” *arXiv preprint arXiv:1301.3781*, 2013. [Online]. Available: https://arxiv.org/abs/1301.3781

[2] S. Westman et al., “Artificial Intelligence for Career Guidance – Current Requirements and Prospects for the Future,” *IAFOR Journal of Education: Technology in Education*, vol. 9, no. 4, pp. 5–25, 2021. [Online]. Available: https://files.eric.ed.gov/fulltext/EJ1318705.pdf

[3] V. Lai, K. J. Shim, R. J. Oentaryo, P. K. Prasetyo, C. Vu, E. P. Lim, and D. Lo, “CareerMapper: An Automated Resume Evaluation Tool,” *arXiv preprint arXiv:1611.05339*, 2016. [Online]. Available: https://arxiv.org/abs/1611.05339

[4] Y. Luo, H. Zhang, Y. Wang, and H. Xu, “ResumeNet: A Learning-based Framework for Automatic Resume Quality Assessment,” *arXiv preprint arXiv:1810.02832*, 2018. [Online]. Available: https://arxiv.org/abs/1810.02832

[5] K. Yao et al., “ResuFormer: Semantic Structure Understanding for Resumes via Multi-Modal Pre-training,” in *Proc. IEEE Int. Conf. Data Engineering (ICDE)*, 2023, pp. 2829–2839. [Online]. Available: https://www.researchgate.net/publication/372674850

[6] D. Shi, T. Wang, H. Xing, and H. Xu, “A learning path recommendation model based on a multidimensional knowledge graph framework for e-learning,” *Knowledge-Based Systems*, vol. 195, 105618, 2020. [Online]. Available: https://doi.org/10.1016/j.knosys.2020.105618

[7] F. L. da Silva et al., “A systematic literature review on educational recommender systems,” *Education and Information Technologies*, vol. 27, pp. 5075–5105, 2022. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9472736/

[8] X. Q. Ong and K. H. Lim, “SkillRec: A Data-Driven Approach to Job Skill Recommendation for Career Insights,” *arXiv preprint arXiv:2302.09938*, 2023. [Online]. Available: https://arxiv.org/abs/2302.09938

[9] D. Çelik Ertuğrul and S. Bitirim, “Job recommender systems: a systematic literature review, applications, open issues, and challenges,” *Journal of Big Data*, vol. 12, no. 140, pp. 1–27, 2025. [Online]. Available: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-025-01173-y

[10] G. Zhu, N. A. Kopalle, Y. Wang, X. Liu, K. Jona, and K. Börner, “Community-Based Data Integration of Course and Job Data in Support of Personalized Career-Education Recommendations,” *arXiv preprint arXiv:2006.13864*, 2020. [Online]. Available: https://arxiv.org/abs/2006.13864